National Aeronautics and
Space Administration

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

Machine Learning Approaches for General Satellite Maneuvers

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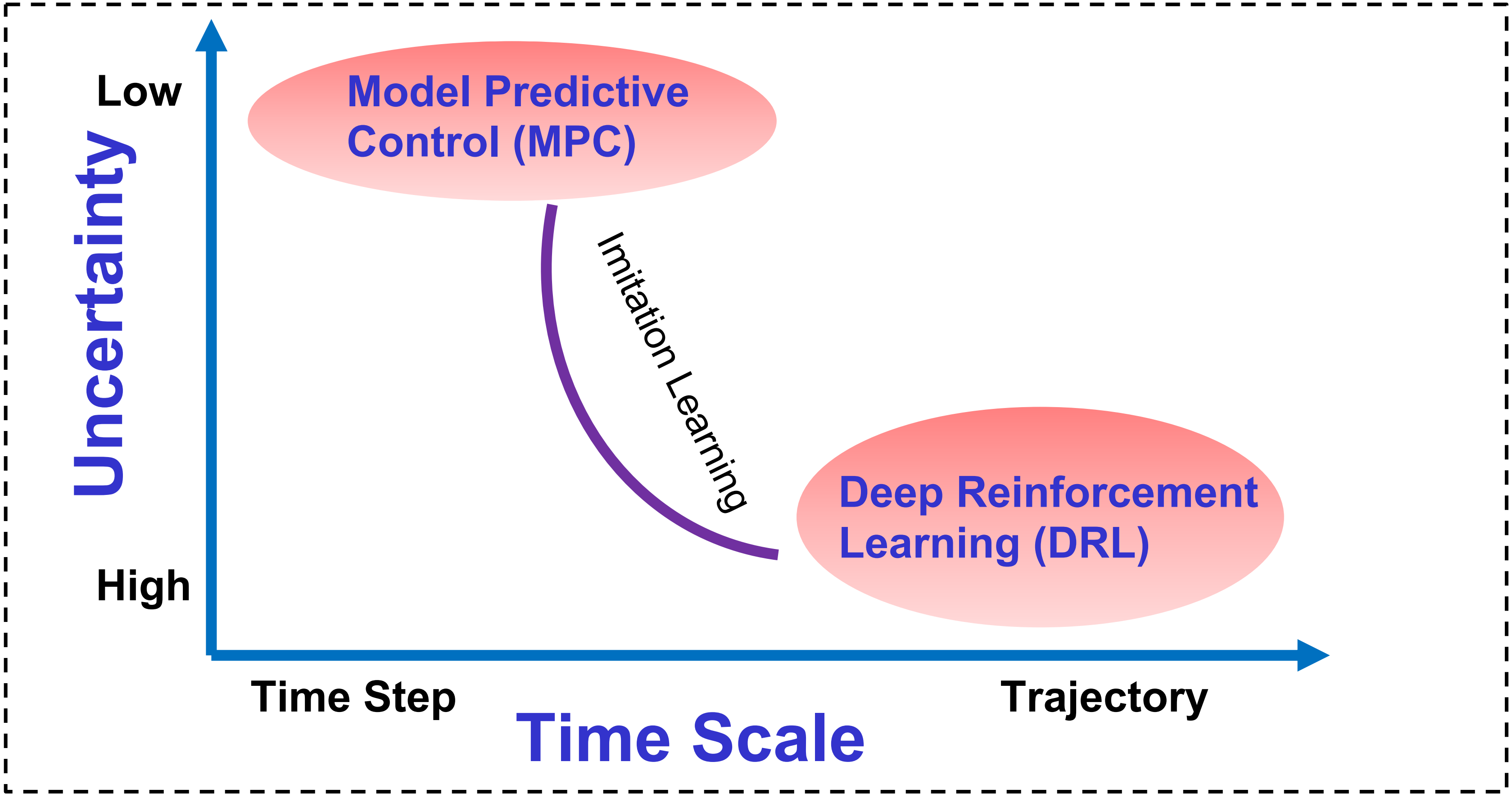
Trade-offs in Decision Making

- Trade off between **uncertainty** and **time scale** of decision making
- Uncertainty play a critical role ⇒ its **representation** is essential
- **Unified** approach/framework for decision making



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Uncertainty Representation and Learning

Finding the optimal policy (non-convex optimization)

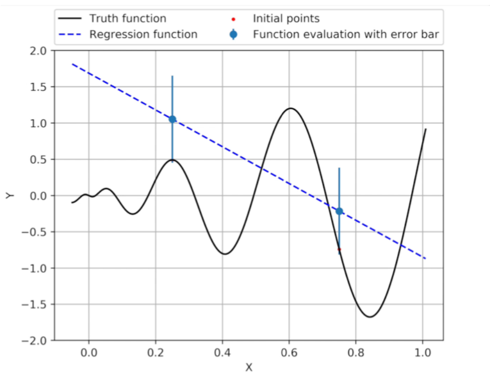
$$\text{minimize } f(x) \text{ with } x \in \Omega$$

Few Data — Machine Learning Approaches — **Many Data**

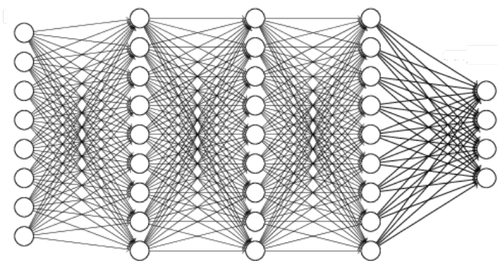
Non-Parametric Methods
Surrogate-based Methods
(e.g., Gaussian Processes (GP), Delta-DOGS, Alpha-DOGS)

Semi-Parametric Methods
Physics Driven Methods + Surrogate-based Methods

Deep Neural Network
Feedforward NN
Recurrent NN



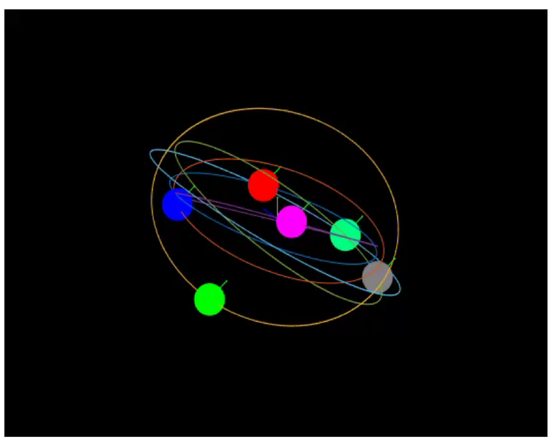
Alimo, Beyhaghi, Bewley, 2017



Case Study: Formation Flying

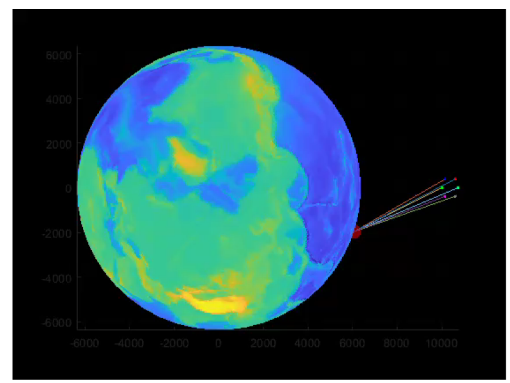
Formation flying → flying individual satellites between fixed states in a local reference frame.

How do we:
- Move satellites between fixed states?
- Minimize fuel?
- Estimate fuel cost in advance?



Credit: JPL-CAST Swarm Autonomy

Goal:
- Generalize undesirable constraints
- Specific formations
- Dynamic models of fixed complexity



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In orbit formation assignment

LVLH (Local Vertical Local Horizontal Reference) Frame

[Rahmani et al 2013, Morgan et al. 2016]

For a satellite in formation flying:

- Relative Position

$$\mathbf{s}_p = (x, y, z)$$

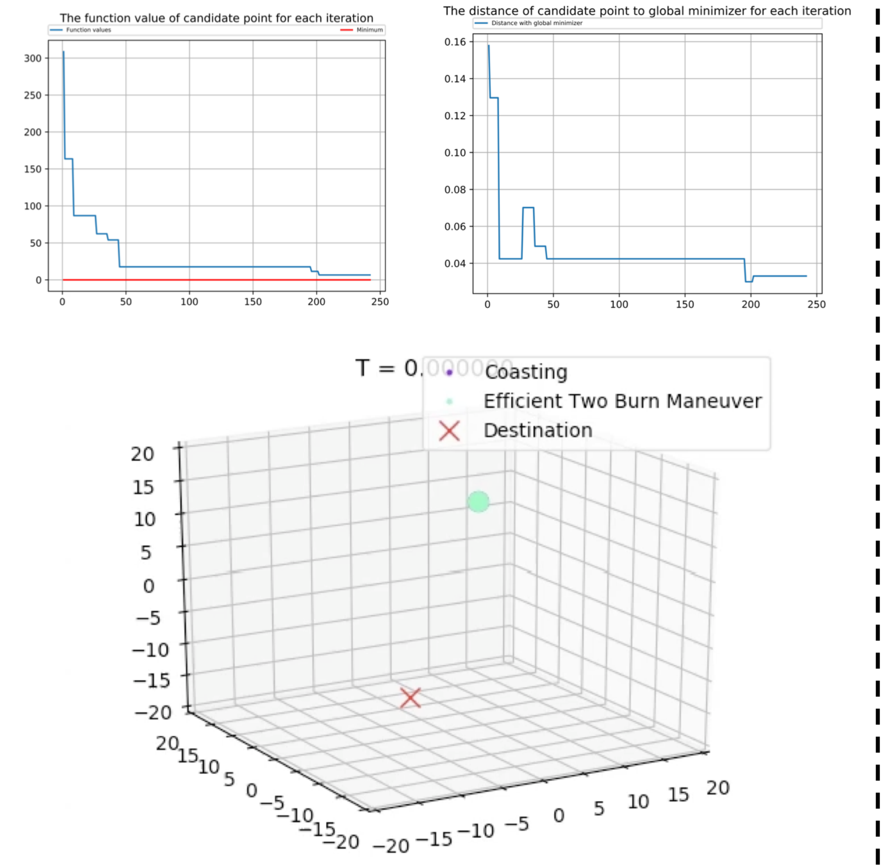
- Relative Velocity

$$\mathbf{s}_v = (\dot{x}, \dot{y}, \dot{z})$$

$$\arg\min_{u} \quad \sum_{t=0}^{T} ||u_t|| + \lambda \, ||\mathbf{s}_T - \mathbf{s}_{dest}||$$

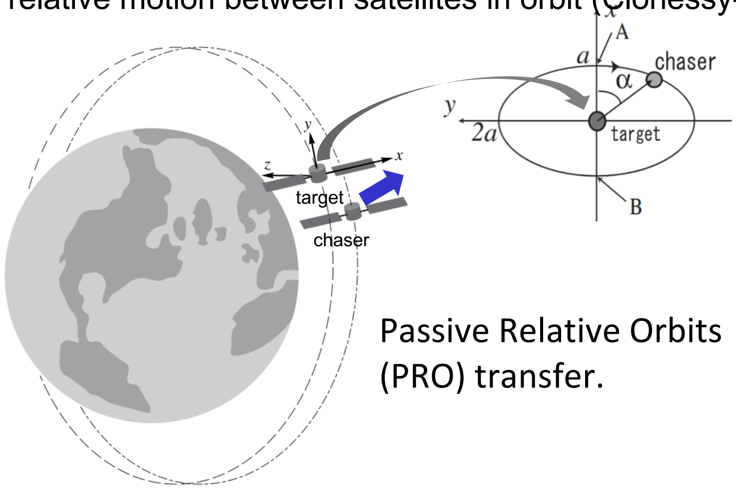
Two-burn maneuver with Delaunay-based optimization (deltaDOGS) in Hill's Frame.

S. R. Alimo et al. "Delaunay-based Derivative-free Optimization via Global Surrogates". JOGO 2018

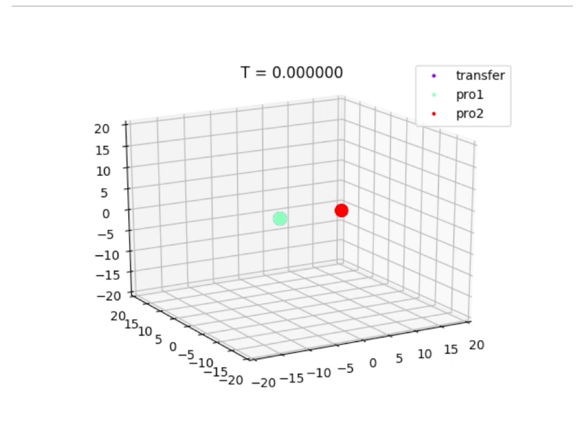


In orbit formation assignment

The relative motion between satellites in orbit (Clohessy-Wiltshire Hill's Equations) [Ichikawa et al. 2008]:.

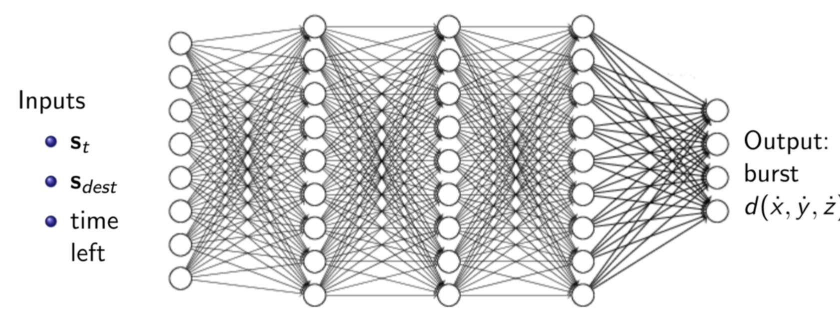


Passive Relative Orbits (PRO) transfer.



Finding the optimal policy, f, for three burn maneuver problem:

- Let $f(\cdot, \theta)$ be a neural network parameterized by $\theta \in R^k$.
- $V(s_t)$ - expected reward starting from state s_t.
- Actor Critic method is used.
- Fully connected neural network to model f.



$$\theta \leftarrow \theta + \alpha \cdot \mathbb{E}_{\text{episodes}}[\Sigma_t(V(\mathbf{s}_t) - \Sigma_{t'=t}^{T} r_{t'})\nabla_\theta \log \text{prob}(f(\mathbf{s}_t; \theta) == a_t)]$$

Summary

Main stream control approaches such as MPC, Sequential Convex Optimization fail in the situations:

1. **Large number of spacecraft are presented**
2. **Optimization involved with full nonlinear dynamics**
3. **Convergence is not guaranteed and is hard to find a bound for the objective function.**
4. **Collison constraints make these problems harder to address and increase uncertainty.**

1. **ML-based approaches showed promising results in dealing with high dimensional problems aka self-driving cars**
2. **Explore and exploit better in the parameter space**
3. **Simulations are highly accurate Reasonably clear choice of rewards**

- **We need a generalizable satellite controller MPC + ML for satellite control**
- **Imitation Learning can be used for online execution for the satellite control**

Acknowledgments & Questions?

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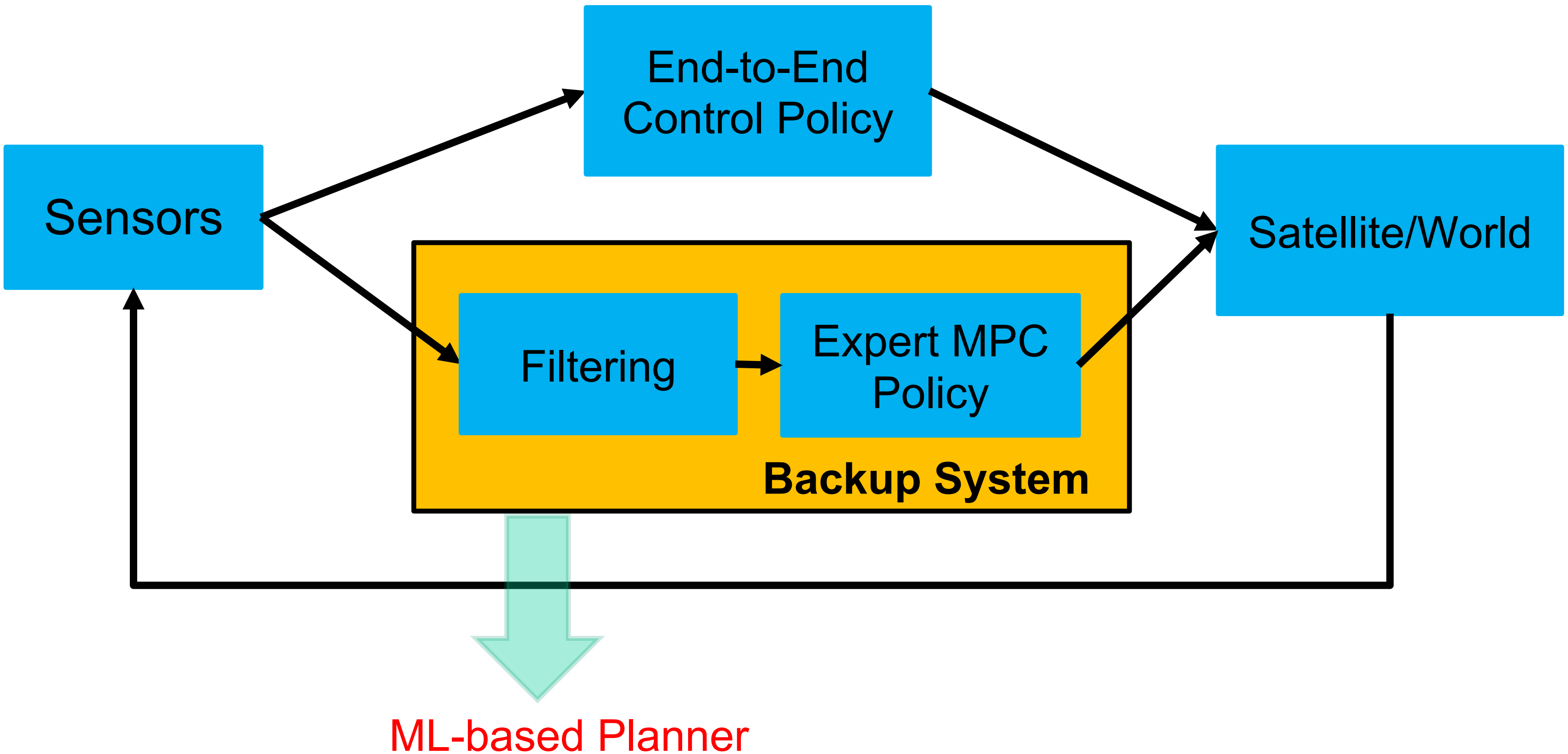
Uncertainty Representation and Learning

In self-navigating spacecraft, due to safety criticality, backup systems are essential.



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Clohessy-Wiltshire Hill's Equations

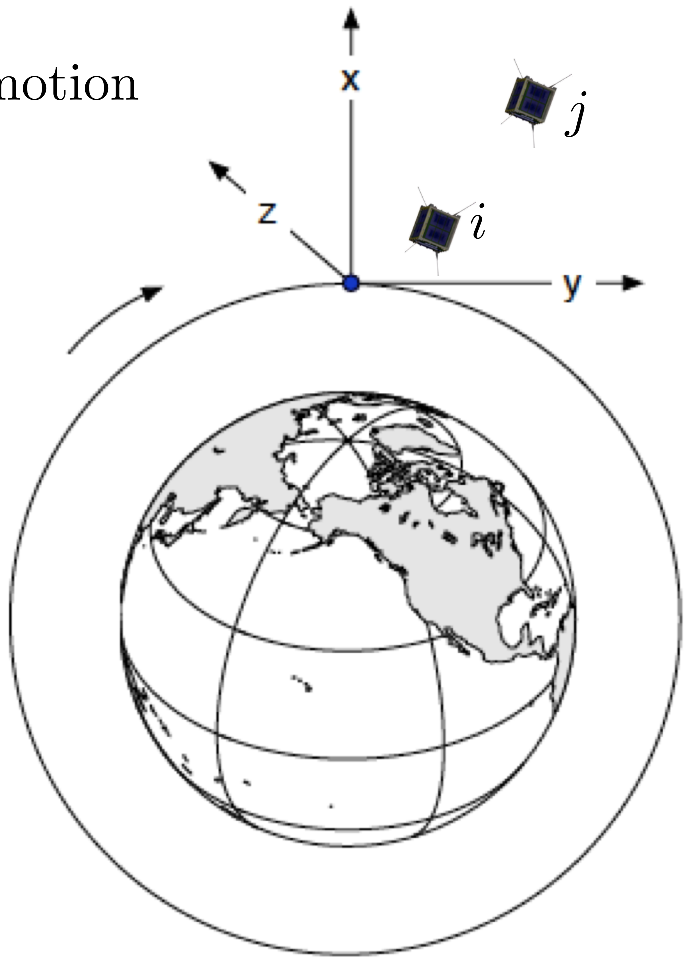
Using Hill's equation for relative S/C motion

$$\dot{x}_i(t) = Ax_i(t) + B_i u_i(t)$$

$$A = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 3n^2 & 0 & 0 & 0 & 2n & 0 \\ 0 & 0 & 0 & -2n & 0 & 0 \\ 0 & 0 & -n^2 & 0 & 0 & 0 \end{bmatrix}$$

Solution of which depends on e^{At}

$$e^{At} = \begin{bmatrix} 4-3\mathcal{C} & 0 & 0 & \frac{\mathcal{S}}{n} & \frac{-2\mathcal{C}+2}{n} & 0 \\ 6\mathcal{S}-6nt & 1 & 0 & \frac{2\mathcal{C}-2}{n} & \frac{-3nt-4\mathcal{S}}{n} & 0 \\ 0 & 0 & \mathcal{C} & 0 & 0 & \frac{\mathcal{S}}{n} \\ 3n\mathcal{S} & 0 & 0 & \mathcal{C} & 2\mathcal{S} & 0 \\ 6n\mathcal{C}-6n & 0 & 0 & -2\mathcal{S} & -3+4\mathcal{C} & 0 \\ 0 & 0 & -n\mathcal{S} & 0 & 0 & \mathcal{C} \end{bmatrix}$$



Ref: Rahmani et al. "Fuel Optimal In Orbit Position Assignment of Formation Flying Spacecraft" 2015